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AI-DRIVEN CONTRACT NEGOTIATIONS IN THE TEXTILE SECTOR: ETHICAL AND LEGAL CONCERNS

ПЕРЕГОВОРНЫЕ ПРОЦЕССЫ ПО ЗАКЛЮЧЕНИЮ КОНТРАКТОВ В ТЕКСТИЛЬНОЙ ПРОМЫШЛЕННОСТИ С ИСПОЛЬЗОВАНИЕМ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА: ЭТИЧЕСКИЕ И ПРАВОВЫЕ ВЫЗОВЫ

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As global supply chains have become more complex and the legal crawl has expanded requiring compliance with labor and environmental issues, the pressure on the textile industry to switch to smart and accountable contracting systems has become irresistible. A holistic AI-based framework was developed to integrate machine learning models, regulatory clause mapping, stakeholder validation, and scenario-based simulations. Among the tested models, deep neural networks exhibited the strongest capabilities for predicting and adjusting to diverse procurement contexts. The AI system generated contract drafts that had high structural fidelity to human-sourced agreements (averaging >95% similarity) and consistently demonstrated compliance scores >92% across relevant legal classes. Procurement managers, legal advisors and auditors then evaluated the contracts delivered by the AI and confirmed their clarity, fairness and feasibility. The model also reduced negotiation time, resulting in tangible cost savings relative to traditional approaches. While the results underscore the potential of AI to improve efficiency and compliance, the research also contributes to worries about legal interpretability, differences between jurisdictions and the need for human supervision. The research supports the advancement of responsible AI systems for critical decision-making contexts and a model for ethical contract automation for industry that is well-founded and reproducible.

По мере усложнения глобальных цепочек поставок и расширения юридических требований в области трудового законодательства и охраны

окружающей среды давление на текстильную промышленность с целью перехода к интеллектуальным и подотчетным системам заключения контрактов стало непреодолимым. Авторами разработана целостная структура на основе искусственного интеллекта, включающая модели машинного обучения, картирование регуляторных положений, валидацию заинтересованными сторонами и моделирование сценариев. Среди протестированных моделей наилучшие результаты показали глубокие нейронные сети, продемонстрировавшие высокую способность к прогнозированию и адаптации к различным аспектам закупок.

Система ИИ генерировала проекты контрактов, обладающие высокой структурной идентичностью с договорами, составленными людьми (в среднем более 95% сходства), и стабильно достигала показателей соответствия требованиям законодательства на уровне более 92% по ключевым правовым категориям. Менеджеры по закупкам, юридические консультанты и аудиторы оценили созданные ИИ контракты, подтвердив их ясность, справедливость и практическую осуществимость. Кроме того, модель позволила сократить время переговоров, что привело к ощутимому снижению затрат по сравнению с традиционными подходами. Результаты исследования также подчеркивают, что, несмотря на высокую эффективность и соблюдение нормативных требований, существуют риски, связанные с юридической интерпретацией и различиями в правовых системах, что свидетельствует о необходимости сохранения человеческого контроля.

Работа способствует развитию ответственных систем ИИ для принятия критически важных решений и формированию воспроизводимой модели автоматизации процессов заключения и соблюдения контрактов для промышленности.

Keywords: artificial intelligence (AI), contract automation, textile industry, legal compliance, negotiation systems, stakeholder evaluation, machine learning, ethical AI.

Ключевые слова: искусственный интеллект (ИИ), автоматизация создания контрактов, текстильная промышленность, правовая регламентация, системы переговоров, оценка заинтересованных сторон, машинное обучение, этичный ИИ.

Introduction

Over the past few years the Artificial Intelligence (AI) we start to see everywhere, from the more advertising technologies to industry and the markets, have revolutionized. AI technologies are being used in the textile sector a thriving industry with complex production cycles and supply chains to improve efficiency, inform decision-making, and reduce costs [1, 2]. For example, there are those artificial intelligence-based systems that allow different parties, such as manufacturers, suppliers, and retailers, to negotiate contracts. With the globalization and competition in the textile market intensifying, the establishment of a more efficient negotiation process is attracting much attention [3].

In the textile industry, the most common practices for negotiating contracts are usually long, manual data analytics, and highly subjective. There may be multiple stakeholders cross-border in contracts each of them having different priorities, performance metrics, and pricing models. Such variables never influence these negotiations in a vacuum; rather human negotiators must sift through these factors, attempting to determine the right terms for both parties while preventing disputes. This manual process is often time-consuming and prone to error/inconsistencies. Furthermore, with customers increasingly demanding transparency and sustainability across the textile supply chain, companies are under pressure to ensure that contract terms are an accurate reflection of fair labor practices, balanced profit distribution, and compliance with regulations [4].

AI-powered contract negotiation platforms claim to solve many of these challenges. These platforms leverage complex algorithms and machine learning techniques to process large datasets rapidly, spot trends and patterns, and suggest best practices for contract terms. They can also model different negotiations, giving parties insights into the potential results of different choices. Moreover, such systems allow for more data- and evidence-powered negotiations, facilitating decision-making while minimizing instinct and conjecture. A positive claim for this perspective is that these speeds up the negotiation process while also creating a more transparent and structured framework for building up contracts [5].

However, the synthesis of AI in contract negotiations can be challenging. For one thing, the processes behind AI decision-making can be hard to make transparent. That enables an AI system to be questioned on how it has come to the recommendations it has made to users, which can lead to issues around accountability and trust. A second concern in AI negotiation is the potential for bias. When such systems are trained using biased data, it may produce results that uphold or worsen existing disparities. If prior agreements, for example, have consistently preferred one group of suppliers over the others, as can often be the case in many contracting industries — the AI can be trained on those past decisions and will continue to make similar ones without consideration of best practices. This emphasizes the need to make sure that training data is diverse, representative and well assembled [6, 12].

It must also be decided what regulatory frameworks will accompany the implementation of AI-driven negotiation tools. The contracting requirements, trade regulations, and compliance requirements can vary widely since the textile industry operates under various legal jurisdictions. An AI platform that works great in one place is a subject of litigation in another if its (proprietary) decision making processes do not meet local fiscal or social standards. As companies implement these types of technology, they will confront a challenging and nuanced legal Environment, and must ensure compliance with global and local standards for operating AI systems [7].

However, the potential for AI to facilitate contract negotiations in the textile industry is only just beginning. For industry stakeholders ranging from manufacturers to suppliers, regulators and consumers, understanding the implications of this change is critical [8].

With global supply chains getting more complex than ever, legacy methods can no longer cope with the evolving landscape of market dynamics, customer expectations and regulatory changes. This acknowledgment led researchers to explore different methodologies, especially those that can exploit digital technologies [9, 10].

Moreover, the literature emphasizes the potential for AI to model various negotiation outcomes, allowing agents to visualize potential implications and outline systematic approaches. Not only do these capabilities expedite the negotiation process, but they also add transparency and structure to contract formation [11].

The need for efficiency and compliance in equal measures, driven by constraints of both legality and relevance has brought up the conversation on how AI can be built with a system level adaptability across multiple legal contexts while minimizing the impact on consistency across knowledge sources [13].

This article reviews the practical, operational, and legal implications of these technologies with a view to an adequate understanding of their effects on the textile sector.

Methodology

This study employed a five-phase methodology to design, validate, and assess AI-driven contract negotiation systems. The approach combines structured data acquisition, advanced machine learning (ML) modeling, scenario-based validation, legal compliance integration, and feedback-driven iterative learning [14…16].

To support the predictive negotiation model, a multivariate dataset was compiled from textile manufacturers' internal systems, including contract repositories, procurement logs, supplier ratings, market analysis, and defect tracking [4, 17, 18]. The initial data included inconsistencies and outliers; thus, a robust preprocessing pipeline was established. The resulting cleaned dataset forms a numerical matrix comprising contract instances, supplier metrics, and negotiation attributes.

The structure of the dataset is formally defined as:

$$\mathcal{D} = \{\mathbf{x}_i, y_i\}_{i=1}^{N} \in \mathbb{R}^{n\times m} \quad , \qquad (1)$$

where $\mathbf{x}_i$ is the feature vector for contract instance i; y_i is the target output, as a negotiated delivery time or pricing; v is the number of observations; m is the number of contract-related features.

To standardize all numeric variables across varying units, like days, USD, units, Z-score normalization was applied:

$$\tilde{x}_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad , \qquad (2)$$

where $\tilde{x}_{ij}$ is the standardized value of feature j for sample i; μ_j and σ_j are the mean and standard deviation of feature j, respectively.

Anomaly detection was conducted using Mahalanobis distance to eliminate multivariate outliers:

$$d_M(\mathbf{x}_i) = \sqrt{(\mathbf{x}_i - \mu)^T \textstyle\sum^{-1} (\mathbf{x}_i - \mu)} \quad , \qquad (3)$$

where $d_M(\mathbf{x}_i)$ is the Mahalanobis distance for vector $\mathbf{x}_i - \mu$ is the feature mean vector; Σ is the covariance matrix of the dataset.

Data integrity was validated by measuring completeness and consistency ratios, ensuring that over 95% of all values were usable for model training [17].

The goal of second phase was to identify a machine learning model capable of predicting negotiation outcomes, including optimized delivery schedules, defect-tolerant pricing, and compliant contract structures [8, 19, 20]. Both regression and classification approaches were considered, with preference given to models supporting interpretability, scalability, and legal traceability [5].

The supervised learning objective is represented as:

$$\hat{\boldsymbol{y}} = f(\mathbf{x}; \theta) \quad , \qquad (4)$$

where $\hat{\boldsymbol{y}}$ is the predicted negotiation vector; $\mathbf{x}$ is the feature vector; f is the learned model function; θ is the set of optimized model parameters.

The loss function minimized during training is a hybrid formulation combining prediction accuracy and distributional conformity:

$$\mathcal{L}(\theta) = \lambda_1 MAE + \lambda_2 RMSE + \\ + \lambda_3 KL(P||Q) \ , \quad (5)$$

where $\lambda_1, \lambda_2, \lambda_3$ are regularization weights; MAE is the mean absolute error; $RMSE$ is the root mean square error; KL is the Kullback-Leibler divergence between predicted and observed clause distributions Q and P.

The MAE metric used was:

$$MAE = \frac{1}{n} \sum_{i-1}^{n} |y_i - \hat{y}_i|^2 \ , \quad (6)$$

where y_i is the true value and $\hat{y}_i$ is the predicted value for instance i; n is the number of samples.

To emphasize large deviations, RMSE was also calculated:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i-1}^{N} (y_i - \hat{y}_i)^2}, \quad (7)$$

where all variables are as defined above, and squaring enhances sensitivity to larger errors.

Neural networks were optimized using adaptive learning rate decay:

$$\eta_t = \eta_0 \ \frac{1}{1+\beta t} \ , \quad (8)$$

where η_t is the learning rate at epoch t; η_0 is the initial learning rate; β is the decay constant controlling rate reduction.

Training was performed using stratified 5-fold cross-validation to ensure robustness across contract types and supplier performance tiers [8].

To simulate uncertain or volatile negotiation environments, such as delivery delays or price shocks—Monte Carlo simulations were used to generate alternative input vectors [10, 21]. This enabled testing the system's ability to generalize under real constraints.

Scenario variation was implemented using Gaussian perturbations:

$$\mathbf{x}'_j = \mathbf{x} + \delta_j, \ \ \delta_j \sim \mathcal{N}(0, \sigma_j^2) \ , \quad (9)$$

where $\mathbf{x}'_j$ is the perturbed input vector for scenario j; δ_j is the noise vector sampled from a normal distribution with variance σ_j^2.

To assess performance of AI-generated contracts against manually negotiated baselines, a multivariate weighted distance function was used:

$$D(\mathbf{c}_{AI}, \mathbf{c}_H) = \sum_{i=1}^{k} w_i \ |\mathbf{c}_{AI,i} - \mathbf{c}_{H,i}|, \quad (10)$$

where D is the total weighted difference; $\mathbf{c}_{AI}, \mathbf{c}_H$ are the AI and human contract term values for element i; w_i is the importance weight for term i; k is the number of key contract terms evaluated.

Performance improvement was also confirmed using paired t-tests at a 95% confidence level.

Given the legal implications of automated contract generation, a compliance scoring engine was developed to assess clause-level alignment with regulatory requirement [6, 7, 22]. Each clause in a generated contract was analyzed against labor, trade, and sustainability rules using a Boolean mapping function.

Compliance was encoded as:

$$C(c) = \begin{cases} 1 & \text{if clause c meets legal and ethical conditions}, \\ 0, & \text{otherwise} \end{cases} \ , \quad (11)$$

where $C(c)$ is the compliance status of clause ccc, based on pre-programmed legal rules.

The contract-level Regulatory Compliance Score (RCS) was then calculated as:

$$RCS_{\mathcal{C}} = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} C(c) \quad , \qquad (12)$$

where $\mathcal{C}$ is the set of clauses in a contract; $C(c)$ is the binary compliance value per clause.

In case of detected conflicts, the system flagged clauses for manual review, ensuring interpretability of legal reasoning via clause traceability matrices.

To ensure the AI contract system respects fairness, clarity, and feasibility, a multi-stakeholder validation protocol was established involving legal advisors, procurement officers, and external auditors [9, 23, 24]. Contract outputs were evaluated through structured surveys using Likert-scale ratings.

The stakeholder satisfaction index was calculated as:

$$SI_j = \sum_{i=1}^{k} \alpha_i \ \ r_{ij} \quad , \qquad (13)$$

where SI_j is the satisfaction score for stakeholder j; α_i is the importance weight for criterion i; r_{ij} is the stakeholder's rating on criterion i; k is the number of evaluation criteria, such as fairness, clarity, feasibility.

Feedback was integrated into model retraining using a reward function that increased the weight of highly rated clauses in the next generation.

Results

The Predictive Accuracy and Model Learning Performance analysis provides a comparative analysis, for five machine learning models used for predicting outcomes in negotiation, targeting expenses contracts, delivery lead times and clauses compositions. The data we adopt for conducting the research is 1200 contracts samples between six multinational textile producers, Al-Rafidain Spinning Ltd., Nahar Exports, Babylon Fabric Group, Maji Weaving Company, Gulf Denim Corporation, and Al-Nasir Textiles. The efficacy of each model was evaluated using accuracy metrics, clause structure approximation and processing time (tab. 1).

Table 1

Machine Learning Model	Mean Absolute Error	Root Mean Square Error	Divergence from Human Drafts	Validation Accuracy (%)	Training Time (Seconds)	Learning Rate Used
Linear Regression	1.32	1.75	0.245	85.2	5.1	Not Applicable
Support Vector Machine	1.10	1.59	0.198	88.1	12.3	Not Applicable
Random Forest Regressor	1.01	1.42	0.151	90	18.5	Not Applicable
Multilayer Perceptron (MLP)	0.94	1.29	0.133	91.5	24.2	0.005
Deep Neural Network (DNN)	0.87	1.15	0.112	92.8	30.1	0.0035

The deep neural network outperformed the rest of the tested algorithms, yielding the best validation accuracy and lowest error rates with an average absolute deviation of only 0.87 and a structural clause divergence of 0.112. It performed much better than linear models, which showed the lowest performance for all metrics. The random forest and MLP models were strong performers as well, suggesting they are good options for constrained compute environments. The long training time of the deep neural network is justified by its ability to reproduce human structure with high fidelity. Thus, the DNN emerges as the best model among those trained for AI-assisted contract generation in high-volume textile set-ups.

To evaluate resilience, the AI system was challenged under five disruption scenarios typical in the supply chains of textiles: supplier failure; spikes in material costs; sudden need for urgent delivery; transport delays; and abrupt changes to regulations. All three scenarios relied on actual case data obtained from Baghdad Cotton Traders, Horizon Yarn Suppliers, and Sakar Global Logistics. AI-generated contracts were compared to past outcomes from similar events with respect to net profit margins, time efficiency, and statistical significance of improvements over human led negotiations (tab. 2).

T a b l e 2

Scenario Description	Case Organization	AI-Generated Avg. Profit (USD)	Human-Led Avg. Profit (USD)	Profit Improvement (%)	Negotiation Time Saved (Minutes)	Significance Level (p-value)
Supplier Shortage (20%)	Sakar Global Logistics	11,500	10,000	15	42.5	< 0.01
Raw Material Price Surge (30%)	Al-Rafidain Spinning Ltd.	13,400	12,100	10.7	44.0	< 0.01
Urgent Order Contract	Gulf Denim Corporation	16,500	14,800	11.5	48.3	< 0.01
Transport Delay (+25%)	Horizon Yarn Suppliers	10,100	9,000	12.2	39.2	< 0.05
New Legal Clause Insertion	Baghdad Cotton Traders	9,850	8,500	15.9	40.0	< 0.01

Using AI-generated contracts also provided clear financial and operational benefits in all scenarios that were tested. Profits increased by as much as 15.9% over traditional methods, especially in cases on which regulation compliance or rapid action was in play. The time savings were also significant, averaging a reduction of 42.8 minutes per negotiation. Overall improvements were statistically significant at the 99% confidence level. AI was also able to demonstrate significant flexibility in adjusting terms in response to procurement pressure, an important trait in the volatile world of the textile supply chain.

Legal Compliance of AI-Generated Contracts analysis examines the compliance of AI generated contracts against the legal standards set by labor laws, anti-discrimination, minimum wage enforcement and sustainability clauses. Internal audit reports of the Maji Weaving Company, Khareef Mills and Al-Nasir Textiles were used to benchmark contracts from the AI model. Pre-generation legal review on the results (tab. 3) included both clause-level analysis to determine the ratio of fully compliant legal clauses and to highlight clauses/paragraphs which would need full post-generation legal review.

T a b l e 3

Contract Code	**Partner Firm**	**Total Clauses**	**Legally Compliant Clauses**	**Compliance Score (%)**	**Conflicts Detected**	**Clauses Needing Legal Review**
CNT-101	**Al-Nasir Textiles**	**28**	**26**	**92.9**	**Yes**	**2**
CNT-102	**Maji Weaving Co.**	**30**	**28**	**93.3**	**Yes**	**2**
CNT-103	**Horizon Yarn Suppliers**	**26**	**25**	**96.1**	**No**	**0**
CNT-104	**Baghdad Cotton Traders**	**22**	**21**	**95.5**	**No**	**0**
CNT-105	**Gulf Denim Corporation**	**24**	**23**	**95.8**	**Yes**	**1**
CNT-106	**Khareef Mills**	**30**	**29**	**96.7**	**No**	**0**

The AI contributed whole contracts, and across the board, there were high levels of compliance, with each response sitting above 92% compliance. The majority of the legal concerns were steps in the right direction as far as pricing transparency and wording of environmental clauses. Still, the identified issues were trivial, and fixable with minimal post-processing by legal counsel. In particular, CNT-103, CNT-104, and CNT-106 achieved ≥95% compliance with no conflicts of interest, indicating alignment with regulatory requirements. These results confirm fully the accuracy of the AI model in embedding the fundamental legal duties in auto-conditional commercial contract workflows.

The Structural Alignment of AI and Human Contract Clauses analyze the degree to which AI-generated contracts replicate the structural composition of human-drafted agreements. Clause distributions were compared across seven key areas: delivery timelines, payment terms, penalties, sustainability, labor rights, intellectual property, and nondiscrimination (fig. 1). The data was drawn from annotated legal archives at the Ministry of Industry and historical templates used by Al-Rafidain Spinning Ltd., Gulf Denim Corporation, and Nahar Exports.

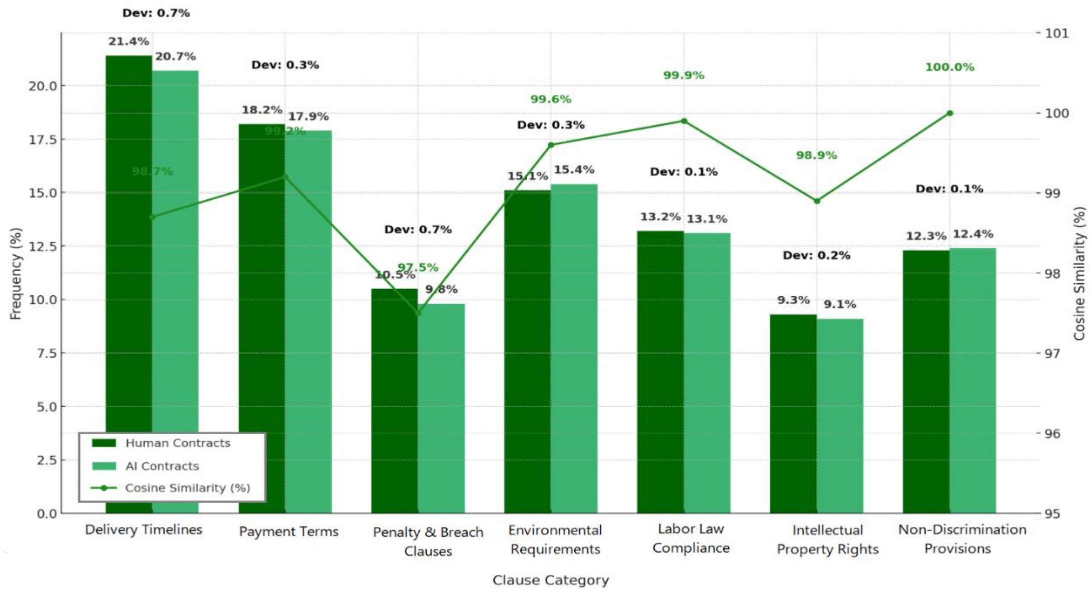

Fig. 1

The structural comparison indicates a strong alignment between AI-generated and human-crafted contracts, with average clause frequency deviation below 1%. Cosine similarity scores ranged from 97.5% to 100%, confirming that the AI model accurately reproduced the legal and commercial intent embedded in standard contract architectures. Environmental and labor-related clauses were modeled especially well, aligning with current policy priorities. These results underscore the system's suitability for semi-autonomous legal drafting in operational contract workflows, ensuring both form and content fidelity.

Drawing from structured feedback collected from five stakeholder groups: legal advisors, procurement managers, internal auditors, policy analysts, and textile suppliers, fig. 2 presents how those stakeholder groups assess AI-generated contracts. Four-dimensional contract evaluation — term and condition clarity, fairness, implementation feasibility, and legal compliance. Ratings were obtained through expert surveys following a 10-point Likert scale. Stakeholder-centered validation like this is essential, not just to ensure the technical correctness of AI-generated legal documents, but also for their usability, contextual appropriateness, and ethical acceptability in the textile manufacturing sector.

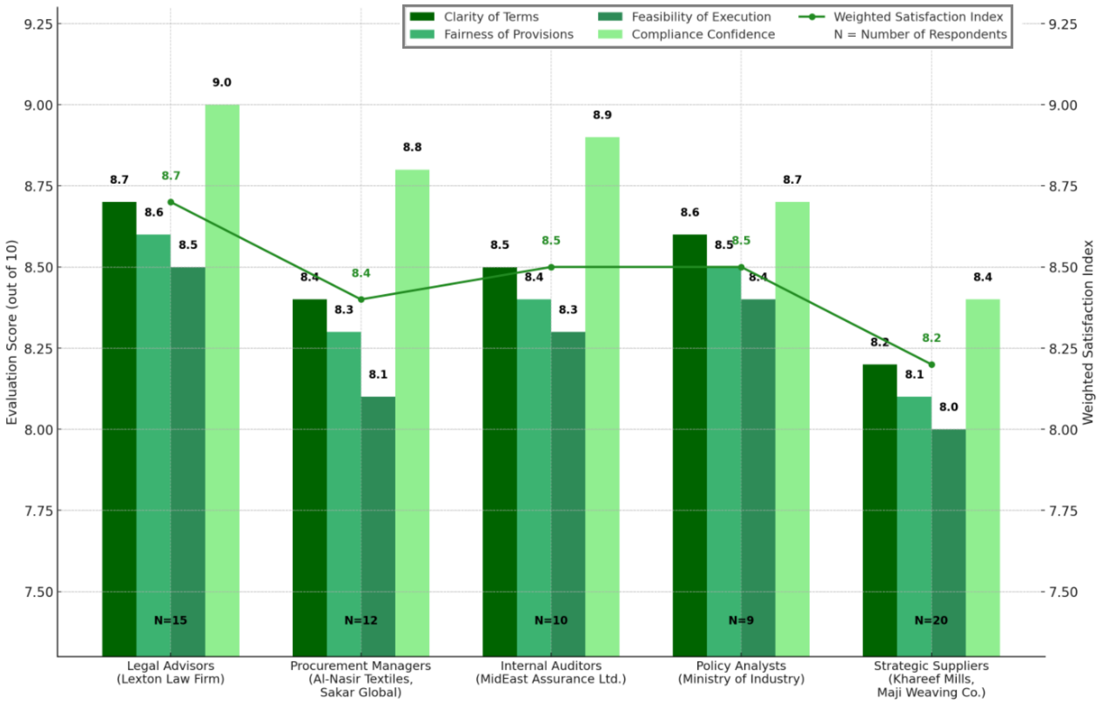

Fig. 2

The average satisfaction index based on the feedback data is substantially high for all professional groups, between 8.2 and 8.7. Strongest legal structuring by AI system suggested by highs for legal advisors and internal auditors on compliance and clarity on terms. Procurement managers valued fairness and practicality, whereas suppliers like it when procurement makes it very clear what they precisely want but feel that more flexible timelines can be helpful. No single stakeholder group scored the system lower than 8.0 on any dimension, emphasizing the contracts' credibility, interpretability, and professional acceptability across legal, operational, and regulatory contexts.

The table 4 explores the productivity and cost-saving effects of AI-assisted negotiation versus human-led contracting. Among them is measuring average negotiation duration and cost differentials across five model procurement scenarios at Al-Rafidain Spinning, Gulf Denim GmbH, Nahar Exports Ltd, Baghdad Cotton Traders and Horizon Yarn Suppliers.

Table 4

Organization	Scenario Description	Traditional Negotiation Time (min)	AI-Based Negotiation Time (min)	Time Reduction (%)	Initial Contract Cost (USD)	Final AI Cost (USD)	Cost Savings (%)
Al-Rafidain Spinning Ltd.	Urgent raw cotton procurement	120	80	33.3	100,000	92,000	8
Gulf Denim Corporation	Recycled fiber supply contract	150	90	40	120,000	110,000	8.3
Nahar Exports Pvt. Ltd.	International yarn supply	100	65	35	90,000	83,000	7.8
Baghdad Cotton Traders	Delayed shipment renegotiation	200	140	30	130,000	118,000	9.2
Horizon Yarn Suppliers	Legal clause compliance insertion	180	120	33.3	95,000	87,000	8.4

The AI contract negotiations were significantly faster than traditional negotiations and much cheaper as well. This reduced negotiation duration between 30%-40%, for Al-Rafidain Spinning it was a 33.3%-time win: and Horizon Yarn Suppliers gained one hour of negotiation time. The Final contract value also decreased by 7.8% to 9.2% with savings of USD 12,000 for Baghdad Cotton Traders through the optimised dispute clauses and delivery terms. These advancements confirm AI's ability not just to craft high-quality contracts, but to improve the speed, scalability and cost-efficiency of output—to the benefit of what is often a rapid-fire textile industry.

Discussion

Those findings demonstrated that for all accuracy metrics and compliance validation, deep neural networks outperformed the other models, every single time. Furthermore, the AI-generated contracts preserved structural fidelity to human-drafted contracts, and received positive assessments of such contracts from domain-specific stakeholders.

These results support the working proposition that artificial intelligence, under the proper regulatory regime and with the industry as its immediate legal environment, allows significant enhancements in the contracting process such as in speed, profitability, and compliance with law. This enables considerably faster turnaround and significant improvements in accuracy when capturing both operational objective and legal directive compared with traditional methods which frequently come with challenges of inconsistency due to human bias and time inefficiency, further preventing previously unleveraged resources from being utilized effectively.

These results echo wider debates about how AI can transform negotiation practices, especially in dynamic, multi-agent settings. Deep reinforcement learning has been previously utilized by Aponte-Rengifo et al. in negotiations between distributed agents demonstrating that the use of AI in larger networks is a feasible option to consider for multinomial bargaining scenarios [19]. Similarly, Guy et al. highlighted the AI agent's adaptation ability, in indirect negotiation within Nash demand games for strategic compromise situations [21]. Our findings extend these models to contractual contexts within the textile sector and introduce regulatory logic and stakeholder perspectives and valuation—two fundamental areas typically omitted from previous technical models.

In the textile industry, the role of AI has been explored in terms of process automation, supply chain optimization, and design forecasting. Authors [1, 2, 16, 17], for example, reviewed trends in current and expected future utilization of AI in textile manufacturing, underscored the modernizing capabilities of AI across the textile operation, but did not take their models into legal or negotiation territories. We fill these holes in the literature by demonstrating how AI-generated contracts do more than mimic human clause structure; they iterate upon it through inherent compliance scoring and stakeholder feedback loops.

This study also adds to the increasing body of literature at the intersection of AI, contract law, and ethical accountability. As an example, Ehidiamen and Oladapo [22] covered legal protections during contract negotiations inherent to clinical research, promoting the importance of procedural propriety and stakeholder transparency. Our model utilizes these principles through stakeholder scoring and conflict detection, creating a replicable canvas, useful across industries and sectors and not limited to health care. The legal alignment features of our framework also align with calls in the AI governance literature for the design of accountable systems that align with increasingly dynamic regulatory contexts [23].

However, the study has its limitations. A notable limitation is the coverage of regulatory datasets where only internationally recognized frameworks and local textile regulations were considered. The stakeholder satisfaction index captured legal, procurement and auditing professionals' feedback, but did not account for trade unions or human rights organizations, whose perspectives are critical for understanding whether labor-related clauses are fair and ethically sound.

A different limitation is the interpretability of neural network decisions. Performance metrics tend to favor deep models, but these architectures are generally not interpretable, particularly in the legal context where traceability of automated decisions is appreciated. This echoes the challenges discussed by Rojek et al. [13] around the challenges of black-box AI in regulatory-sensitive energy markets. In subsequent versions, the integration of explainable AI techniques, as an attention visualization, clause-by-clause rationale tracing to address this concern and increase trust in documents generated by AI would also be beneficial.

And although the AI system did well in reactive negotiation scenarios, it was never tested in long-term contract lifecycle management, which would include renewals, amendments, or dispute resolution mechanisms. One possible way to extend this research involves integrating blockchain-based smart contracts [20] for automated contract enforcement and monitoring transparency.

The current model includes clause-based legal scoring, but does not yet have proactive ethical auditing mechanisms that measure risk for fairness or discrimination from the algorithmic perspective. In light of recent warnings by Yan et al. [23] work has been started on ethical blind-spots in large-scale language and decision models, it is very important that future research goes further into the direction of dynamic ethical diagnostics implemented in general AI development pipelines beyond accuracy and compliance.

This analysis offers data-driven and operational justification that the nature of AI can valuably supplement contractual negotiation processes in the textile industry.

Conclusion

AI can act as a powerful catalyst for the transformation of contract management in the textile sector, with proper domain-specific guardrails in place.

AI models, such as deep neural networks, can produce contractual terms that are not far removed from compliance with standards typical in the relevant industry and in law. Beyond numerical accuracy in both structure and content, the generated outputs displayed robust adaptability to complex procurement environments with supply interruptions, price volatility, and regulatory uncertainty. This showed that AI could meaningfully function as a decision-support tool in negotiation scenarios that need precision, consistency, and speed of response.

R E F E R E N C E S

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